DOCUMENT RESUME

ED 331 717 SE 052 015

AUTHOR Niaz, Mansoor; Robinson, William R.
TITLE Teaching Algorithmic Problem Solving or Conceptual Understanding: Role of Developmental Level, Mental Capacity, and Cognitive Style.
PUB DATE Apr 91
NOTE 32p.; Paper presented at the Annual Meeting of the National Association for Research in Science Teaching (Lake Geneva, WI, April 7-10, 1991).
PUB TYPE Speeches/Conference Papers (150) -- Reports - Research/Technical (143)

EDRS PRICE MF01/PC02 Plus Postage.
DESCRIPTORS *Algorithms; *Chemistry; *Cognitive Development; *Cognitive Style; *Concept Formation; Higher Education; *Problem Solving; Science Instruction

ABSTRACT

It has been shown previously that many students solve chemistry problems using only algorithmic strategies and do not understand the chemical concepts on which the problems are based. It is plausible to suggest that if the information is presented in differing formats the cognitive demand of a problem changes. The main objective of this study (involving 62 students in a chemistry course at Purdue University, Indiana) is to investigate the degree to which cognitive variables, such as developmental level, mental capacity, and disembedding ability explain student performance on problems which: (1) could be addressed by algorithms; or (2) require conceptual understanding. All conceptual problems used in this study were based on a figurative format. The results obtained show that in all four problems requiring algorithmic strategies, developmental level of the students is the best predictor of success. This could be attributed to the fact that these are basically computational problems, requiring mathematical transformations. Although all three problems requiring conceptual understanding had an important aspect in common (the figurative format), yet in all three the best predictor of success is a different cognitive variable. It was concluded that: (1) the ability to solve computational problems (based on algorithms) is not the major factor in predicting success in solving problems that require conceptual understanding; (2) solving problems based on algorithmic strategies requires formal operational reasoning to a certain degree; and (3) student difficulty in solving problems that require conceptual understanding could be attributed to different cognitive variables. (32 references) (Author/KR)

TEACHING ALGORITHMIC PROBLEM SOLVING OR CONCEPTUAL UNDERSTANDING: ROLE OF DEVELOPMENTAL LEVEL, MENTAL CAPACITY, AND COGNITIVE STYLE

MANSOOR NIAZ

CHEMISTRY DEPARTMENT, UNIVERSIDAD DE ORIENTE

APARTADO POSTAL 90, CUMANA, ESTADO SUCRE, VENEZUELA

and

WILLIAM R. ROBINSON

DEPARTMENT OF CHEMISTRY, PURDUE UNIVERSITY

WEST LAFAYETTE, INDIANA 47907

Paper presented at the 64 Annual Conference of the National Association for Research in Science Teaching (NARST), Lake Geneva, Wisconsin, April 7-10, 1991.

ABSTRACT

It has been shown previously that many students solve chemistry problems using only algorithmic strategies and do not understand the chemical concepts on which the problems are based. It is plausible to suggest that if the information is presented in differing formats the cognitive demand of a problem changes. The main objective of this study is to investigate the degree to which cognitive variables, such as developmental level, mental capacity, and disembedding ability explain student performance on problems which: a) could be addressed by algorithms or b) require conceptual understanding. All conceptual problems used in this study were based on a figurative format. The results obtained show that in all four problems requiring algorithmic strategies, developmental level of the students is the best predictor of success. This could be attributed to the fact that these are basically computational problems, requiring mathematical transformations. Although all three problems requiring conceptual understanding had an important aspect in common (the figurative format), yet in all three the best predictor of success is a different cognitive variable. It was concluded that: a) the ability to solve computational problems (based on algorithms) is not the major factor in predicting success in solving problems that require conceptual understanding; b) solving problems based on algorithmic strategies requires formal operational reasoning to a certain degree; c) student difficulty in solving problems that require conceptual understanding could be attributed to different cognitive variables.

INTRODUCTION

According to Renner (1982), ".... science education is a discipline devoted to discovering how to lead students to learn to investigate the natural world" (p. 710). Similarly, the Educational Policies Commission (1961) has recognized the importance of, "the development of the ability to think" (p. 12), as the central purpose of education. In spite of these objectives, a major concern of the educational system is to ensure that students learn how to apply algorithms to solve routine problems. According to Herron (1988), "Students manipulate symbols according to memorized rules without connecting the symbols with the macroscopic events and the microscopic models that the symbols represent" (p. 21). The fact that most of our students can manipulate equations, find derivatives, and apply algorithms, yet fail to comprehend qualitative descriptions of real world every day problems, is an indicator of an educational system that focuses on manipulative skills. It is a cause for concern that even many science majors may be slipping through their education with good grades but with little conceptual understanding (Rosnick and Clement, 1980).

Various studies (Anamuah-Mensah, 1986; Ben-Zvi, Eylon, & Silberstein, 1986; Gabel & Sherwood, 1984; Gabel, Sherwood, & Enochs, 1984; Mitchell & Kellington, 1982; Novick & Nussbaum, 1978) have shown that many students solve chemistry problems using only algorithmic strategies and do not understand the

chemical concepts on which the problems are based. More recently, Nurrenbern & Pickering (1987) reported a study in which students were asked to solve both a computational problem on gases and a question that had no mathematical calculation but asked for a purely conceptual understanding of one critical attribute of gases, i.e., they occupy the entire volume of the container. The results obtained show that about two-thirds of the students solved the computational problem, whereas only about one-third of the students solved the problem based on conceptual understanding. Similar results were obtained with stoichiometry problems. Sawrey (1990) has replicated the study with similar results. Both Nurrenbern and Pickering (1987) and Sawrey (1990) attribute these results to the fact that for most teachers the use of algorithmic solution strategies (plug-and-chug) is a major behavioral objective of freshman chemistry. Niaz (1989a) has emphasized that the use of algorithms may decrease the M-demand (amount of information processing required) of a problem, but it does not necessarily facilitate conceptual understanding.

In recent years various studies (Chandran, Treagust, & Tobin, 1987; Lawson, 1983; Mitchell & Lawson, 1988; Niaz, 1987a, 1987b; 1988; Niaz & Lawson, 1985; Staver & Jacks, 1988) have shown that achievement in science depends on cognitive variables, such as developmental level, mental capacity, and cognitive style of the students. Thus it would be interesting to study the cognitive demands of problems that can be addressed by algorithmic solution strategies or that require conceptual

understanding.

PURPOSE

Results obtained by Nurrenbern and Pickering (1987) show a significant ($p < 0.05$) decrease in performance on items requiring conceptual understanding as compared to those that can be solved by algorithmic strategies. All items that required a conceptual understanding were based on presenting the information in a figurative format. In view of the importance of cognitive variables to science achievement, it is plausible to suggest that the cognitive demand of an item changes if the information is presented in differing formats. For example, Lawson (1983) has pointed out the difference between typical multiple-choice test items that seem largely to require knowledge of specific facts and concepts and computational test items that seem to require the ability to transform data in various ways to generate solutions, i.e., formal operational reasoning. Although all items used in the present study had the multiple-choice format, their cognitive demand could vary due to the inclusion of the figurative aspect, which requires additional disembedding and information processing. The main objective of this study is to investigate the degree to which cognitive variables, such as developmental level, mental capacity, and disembedding ability explain student performance on problems requiring use of either algorithms or conceptual understanding.

METHOD

Sixty two students (Ss) enrolled in one section of Chemistry 100, a preparatory course for prospective science and engineering Ss, at Purdue University were selected for study (Mean age = 19.0 years; SD = 1.3 years; males = 32; females = 30) and the section was taught by one of the authors. These Ss were not ready to take the university level general chemistry course because of one or more of the following reasons: weak math skills as indicated by low high school math scores, an inadequate number of high school math courses, or poor performance on the Purdue math placement examination; no high school chemistry experience; and/or an extended layoff between previous schooling and their admission to the university. The text used in the course is Understanding Chemistry, 2nd Edition, (Herron, 1986). Instead of the traditional expository method of instruction a more interactive and participatory approach was adopted.

All Ss were tested to determine the following cognitive predictor variables:

a) Developmental Level:

Group Assessment of Logical Thinking, GALT (Roadrangka, Yeany, and Padilla, 1983) was used to assess this variable. As suggested by these authors a shorter version with 12 items was used, which includes 2 items of each of the following types of reasoning: conservation, proportions, controlling variables,

probability, correlations, and combinations. Ss had to respond correctly on both the question and the reason, in order to receive two points for each item. Of the Ss, 1 scored in the 0-6 range, 13 in the 7-12 range, 33 in the 13-18 range, and 15 in the 19-24 range. The original reliability of the test was 0.85, and for the present sample a split-half reliability coefficient of 0.51 was found.

b) M-capacity:

The Figural Intersection Test, FIT (Pascual-Leone & Burtis, 1974) was used to determine M-capacity. The FIT was originally developed and validated by Pascual-Leone (1969) and its reliability has been found to be generally in the 0.80s when administered to fairly heterogeneous Ss. Detailed descriptions of the test, its administration and scoring procedures are provided by de Ribaupierre and Pascual-Leone (1979) and Pascual-Leone and Smith (1969). The FIT is a group administered paper and pencil test, including 36 items, with no time limit. For each item the Ss must place a point marking the interaction of from two to eight overlapping figures. An item with seven overlapping figures theoretically requires a M-capacity of six for successful completion. 6 Ss had a M-capacity of 4; 20 a M-capacity of 5; 33 a M-capacity of 6; and 3 a M-capacity of 7. A split-half reliability coefficient of 0.61 was computed for the present sample.

c) Disembedding Ability:

Degree of field dependence/field independence was assessed

according to standardized procedure with the timed Group Embedded Figures Test, GEFT (Witkin, et al., 1971). Of the Ss, 16 scored in the 0-6 range (field dependent, FD), 17 in the 7-12 range (field medium, FM) and 29 in the 13-18 range (field independent, FI). A split-half reliability coefficient of 0.69 was found for the present sample.

Experimental Design and Procedure

All four experiments conducted in this study were based on the final exam during the 17th (last) week of the semester and used multiple-choice questions. Questions with figurative aspects were familiar to the students. They had been used on two previous exams and three quizzes. All experiments included at least one problem that required conceptual understanding and another that could be addressed by an algorithmic solution strategy. The two types of problems appeared quite closely, one after the other, on the exam. All items were scored on the basis of correct response (1 point) and incorrect response (0 point).

Experiment 1

This experiment is based on the following three items, 1A, 1B, and 1C, that appeared as items 41, 42, and 43 respectively on the final exam:

Item 1A:

A cylinder contains chlorine gas (mole mass, 70.9 g/mole) at a pressure of 4.0 atmospheres and a temperature of 35^{o} C. What is the pressure of chlorine gas at 130^{o} C?

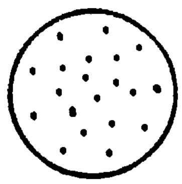
(a) 1.1 atm (b) 3.0 atm

(c) 5.2 atm　　　　　　(d) 15 atm

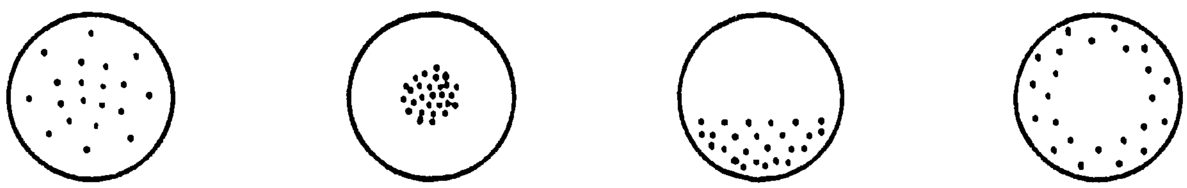
(e) The problem cannot be solved without the mass of chlorine or the volume of the cylinder.

Item 1B:

The figure represents a steel tank holding hydrogen gas at 20^{o} C and 3 atmospheres pressure (the dots represent hydrogen molecules).



Which of the following represents the distribution of hydrogen molecules if the temperature is lowered to -20^{o} C?



(a)　　(b)　　(c)　　(d)

Item 1C:

What is the pressure in atmospheres in a container with a volume of 3.00 liters that contains 35 grams of CO_2 at a

temperature of 400 kelvin? (R = 8.31 L kPa/mole K; 0.082 L atm/mole K; or 62.4 L torr/mole K).

(a) 8.7 atm (b) 14 atm (c) 15 atm

(d) 382 atm (e) 881 atm

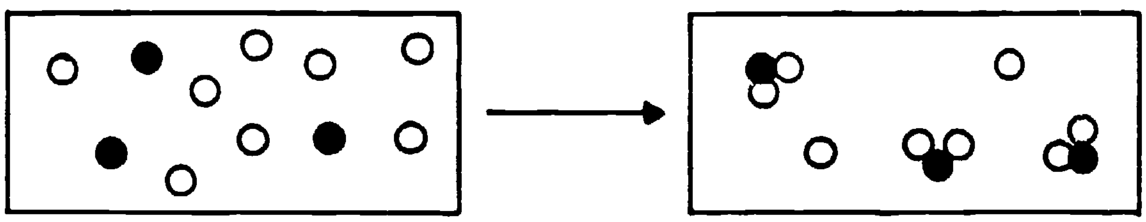
Item 1B was adapted from Nurrenbern and Pickering (1987).Item 1B requires conceptual understanding, whereas Items 1A and 1C can be addressed by algorithmic solution strategies.

Experiment 2

This experiment is based on the following two items, 2A, and 2B, that appeared as items 33 and 36 respectively on the final exam:

Item 2A:

The reaction of a sample of element X (●) with a sample of element Y (o) is represented in the following figure:



Which chemical equation describes the chemical change?

(a) 3 X + 8 Y -----> X_3Y_8

(b) 3 X + 6 Y -----> X_3Y_6

(c) X + 2 Y -----> XY_2

(d) 3 X + 8 Y -----> 3 XY_2 + 2Y

(e) X + 4 Y -----> XY_2

Item 2B:

Calculate the mass of PCl_3 produced when 1.00 gram of P reacts with Cl_2.

2 P + 3 Cl_2 -----> 2 PCl_3

(a) 1.93 g (b) 2.96 g (c) 3.87 g

(d) 4.44 g (e) 6.65 g

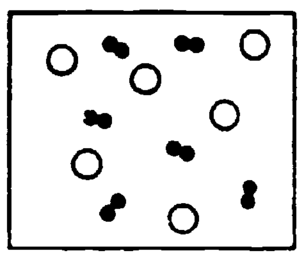
Item 2A was adapted from Nurrenbern and Pickering (1987). Item 2B can be addressed by an algorithmic solution strategy, whereas Item 2A requires conceptual understanding.

Experiment 3

This experiment is based on the following two items, 3A, and 3B, that appeared as items 35 and 37 respectively on the final exam:

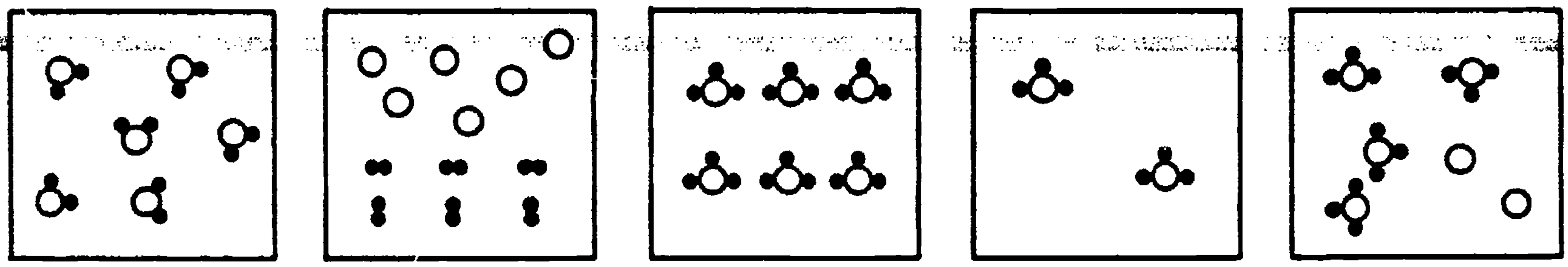
Item 3A:

The equation for a reaction is 2 S + 3 O_2 -----> 2 SO_3. A mixture of S (o) and O_2 (●●) is in a closed container as illustrated in the following figure:



Which of the following represents the mixture of products

after the reaction has occured?



(a) (b) (c) (d) (e)

Item 3B:

The reaction of hydrogen with oxygen is described by the equation: $2\ H_2 + O_2 \text{ ------> } 2\ H_2O$

When a mixture of 2 moles of H_2 and 2 moles of O_2 are combined, what is the limiting reagent and how many moles of the excess reactant remain after the reaction is complete?

	Limiting Reactant	Excess Reactant Remaining
(a)	O_2	1 mole O_2
(b)	O_2	1 mole H_2
(c)	H_2	1 mole O_2
(d)	H_2	1 mole H_2

(e) No reaction occurs since the equation does not balance with 2 H_2 and 2 O_2.

Items 3A and 3B were adapted from Nurrenbern and Pickering (1987). Item 3B can be addressed by an algorithmic solution strategy, whereas Item 3A requires conceptual understanding.

RESULTS AND DISCUSSION

Experiment 1

Table 1 shows that for both Items 1A and 1C (which are readily solved by algorithmic strategies), the mean score of the Ss is higher than on Item 1B, which requires conceptual understanding. Mean score on Item 1A is significantly ($t = 3.38$, $p = 0.001$) greater than on Item 1B. Similarly, mean score on Item 1C is significantly ($t = -11.35$, $p = 0.0001$) greater than on Item 1B. Table 2 shows that performance on Item 1A does not correlate significantly with any of the cognitive predictor variables. Performance on Item 1C correlates significantly only with the developmental level (GALT) of the Ss, whereas performance on Item 1B correlates significantly only with disembedding ability (GEFT). Table 3 shows that the GALT is the best predictor of success on Items 1A and 1C, explaining 5.7% and 14.9% of the variance, respectively. On the other hand, GEFT is the best predictor of success on Item 1B, explaining 8.6% ($F = 5.64$, $p < 0.05$) of the variance. Although all items had the multiple-choice format, Items 1A and 1C are basically computational items, whereas Item 1B does not require any computation. The role of the developmental level (GALT) of the Ss in predicting success on Items 1A and 1C, could be attributed to mathematical transformations that are important in ".... computational test items where the ability to generate logico-mathematical solutions

is more important" (Lawson, 1983, p. 127). The negligible role of M-capacity (FIT) in explaining performance on Items 1A and 1C could perhaps be attributed to the use of algorithms, which decreases the amount of information processing required (i.e., M-demand; cf. Niaz, 1989a; Pascual-Leone, et al., 1978; Pascual-Leone & Niaz, 1988). The fact that disembedding ability (GEFT) is the best predictor of success on Item 1B indicates that among other factors the presence of a 'field effect' (cf. Niaz, 1989b; Pascual-Leone, 1988) determines Ss performance. Although there is only a moderate correlation ($r = 0.29$, $p < 0.05$) between the GEFT and performance on Item 1B, it is important to observe the following: (a) Of all Ss who responded correctly (10 out of 62), 80% were field independent (FI), and only 10% field medium (FM) and field dependent (FD), respectively; and (b) 27.6% (8 out of 29) of the FI Ss responded correctly, whereas only 5.9% (1 out of 17) of the FM and 6.3% (1 out of 16) of the FD Ss responded correctly.

Two further regression analyses were conducted. First, performance on Item 1A and the cognitive predictor variables (GALT, GEFT, & FIT) were introduced into the step-wise regression equation as independent variables, whereas performance on Item 1B remained as the dependent variable. It was observed that once again, GEFT entered first into the regression equation, explaining the same percentage (8.6%) of the variance, followed by performance on Item 1A, FIT, and GALT, each explaining, 6.5% ($F = 4.56$, $p = 0.037$), 1.9%, and 0.8% of the variance,

respectively. In another regression analysis, performance on Item 1C along with the cognitive predictor variables was introduced into the regression as an independent variable, whereas performance on Item 1B remained as the dependent variable. It was observed that once again, GEFT entered first into the regression equation, explaining the same (8.6%) of the variance, followed by FIT, GALT, and performance on Item 1C, each explaining 1.5%, 0.1%, and 0% of the variance, respectively. It appears that disembedding ability (GEFT) is a very consistent predictor of performance on Item 1B, even in the presence of variables such as performance on Items 1A and 1C.

These results suggest that for items which might be regarded as purely algorithmic but that require mathematical transformations, the developmental level of the Ss is an important predictor of success. On the other hand, for figurative items of type 1B, which might be regarded as testing conceptual understanding, disembedding ability is an important predictor of success. Moreover, the ability to solve the computational problem is not a predictor of success on the related conceptual problem.

Experiment 2

Table 1 shows that mean score on Item 2B is significantly ($t = -5.33$, $p = 0.0001$) greater than on Item 2A. Table 2 shows that performance on Item 2A correlates significantly with M-capacity (FIT), whereas performance on Item 2B correlates significantly with the developmental level (GALT) of the Ss. Table 4 shows that GALT is the best predictor of success on Item 2B, explaining

11.1% of the variance, followed by FIT, which explains 4.9% of the variance. On the other hand, FIT is the best predictor of success on Item 2A, explaining 12.4% ($F = 8.50$, $p < 0.005$) of the variance. It can be observed that performance on Item 2B requiring mathematical transformations is explained by GALT and FIT, even though Ss have available to them algorithmic solution strategies. On the other hand, Ss performance on the concept Item 2A, perhaps reflects the importance of its information processing load (M-demand) and not its figurative aspect.

A further regression analysis was conducted by including the performance on Item 2B along with the cognitive predictor variables (GALT, GEFT, & FIT) as an independent variable, whereas performance on Item 2A remained as the dependent variable. It was observed that once again FIT entered first into the regression equation, explaining the same (12.4%) of the variance, whereas by including all the other variables the total amount of variance explained, increased to only 12.7%. This demonstrates once again that information processing capacity (FIT) is a consistent predictor of performance on Item 2A, and once again performance on the computational problem is not a predictor of success on the conceptual problem.

Experiment 3

Table 1 shows that mean score on Item 3B is significantly ($t = -3.92$, $p = 0.0002$) greater than on Item 3A. Table 2 shows that both Items 3A and 3B correlate significantly only with the

developmental level (GALT) of the Ss. Table 5 shows that on both Items 3A and 3B, GALT is the best predictor of performance, explaining significantly 8.5% and 9.7% of the variance, respectively. These results suggest that in spite of the presence of the figurative aspect (as in Items 1B and 2A) in Item 3A, GALT is the best predictor of success.

A further regression analysis was conducted by including the performance on Item 3B along with the cognitive predictor variables (GALT, GEFT, & FIT) as an independent variable, whereas performance on Item 3A remained as the dependent variable. It was observed that once again GALT entered first into the regression equation, explaining the same (8.5%) amount of variance, followed by performance on Item 3B, GEFT, and FIT, each explaining 3.4%, 1.3%, and 0.4% of the variance, respectively. This demonstrates once again that developmental level (GALT) is a consistent predictor of performance on both Items 3A and 3B, and that computational facility is not the major predictor of success on the conceptual problem.

CONCLUSIONS AND EDUCATIONAL IMPLICATIONS

In all four items (1A, 1C, 2B, & 3B) requiring algorithmic strategies, developmental level (GALT) of the Ss is the best predictor of success. This could be attributed to the fact that these items are basically computational items, requiring mathematical transformations. In each of the three items (1B, 2A,

& 3A) requiring conceptual understanding, the role of the cognitive predictor variables is different. In Item 1B, among other factors it is the field effect that constitutes a constraint on Ss performance, in Item 2A it is the information processing load (M-demand) that constitutes an important constraint, and finally in Item 3A it is the logical structure that explains the maximum amount of variance. Even though all three items requiring conceptual understanding have an important aspect in common, i.e., the figurative aspect, yet in all three the best predictor of success is a different cognitive variable. The results obtained in this study are all the more important in view of the fact that we have used single item achievement measures, which provide,".... a much better understanding of just what mental processes are required to solve the individual achievement item" (Lawson, 1983, p. 123). Lawson (1983) has emphasized that, "In typical achievement tests with many items <u>our ability to specify the mental processes necessary for success diminishes</u> with the number and diversity of additional items" (p. 123, emphasis added).

A major contribution of this study has been 'to specify the mental processes (i.e., cognitive predictor variables) necessary for success', which have important implications for educational practice. It is useful for the science teacher to take the following into consideration:

a) The use of algorithmic solution strategies could require formal operational reasoning (developmental level) to a

certain degree.

b) The degree to which a problem requires conceptual understanding could be a function of different cognitive predictor variables, such as developmental level, mental capacity, and disembedding ability.

c) The advantage of using single item achievement measures, which enables us to specify at least to a certain degree the importance of different cognitive variables.

d) The ability to solve computational problems is not the major factor in predicting success in solving conceptual problems.

REFERENCES

Anamuah-Mensah, J. (1986). Cognitive strategies used by chemistry students to solve volumetric analysis problems. Journal of Research in Science Teaching, 23, 759-769.

Ben-Zvi, R., Eylon, B., & Silberstein, J. (1986). Is an atom of copper malleable? Journal of Chemical Education, 63, 64-66.

Chandran, S., Treagust, D., & Tobin, K. (1987). The role of cognitive factors in chemistry achievement. Journal of Research in Science Teaching, 24, 145-160.

de Ribaupierre, A., & Pascual-Leone, J. (1979). Formal operations and M-power: A neo-Piagetian investigation. In Kuhn, D., Ed., New Directions in Child Development: Intellectual Development Beyond Childhood, San Francisco: Jossey-Bass, Inc.

Educational Policies Commission (1961). The central purpose

of American education. Washington, DC: National Education Association.

Gabel, D.L., & Sherwood, R.D. (1984). Analyzing difficulties with mole-concept tasks by using familiar analogue tasks. Journal of Research in Science Teaching, 21, 843-851.

Gabel, D.L., Sherwood, R.D., & Enochs, L. (1984). Problem-solving skills of high school chemistry students. Journal of Research in Science Teaching, 21, 221-233.

Herron, J.D. (1986). Understanding Chemistry (Second Edition). New York: Random House.

Herron, J.D. (1988). View from the discipline. In Gardner, M., Ed., Towards a Science of Science Education. Hillsdale, NJ: Erlbaum.

Lawson, A.E. (1983). Predicting science achievement: The role of developmental level, disembedding ability, mental capacity, prior knowledge, and beliefs. Journal of Research in Science Teaching, 20, 117-129.

Mitchell, A., & Lawson, A.E. (1988). Predicting genetics achievement in nonmajors college biology. Journal of Research in Science Teaching, 25, 23-37.

Mitchell, H., & Kellington, S. (1982). Learning difficulties associated with the particulate theory of matter in the Scottish Integrated Science Course. European Journal of Science Education, 4, 429-440.

Niaz, M. (1987a). Relation between M-space of students and M-demand of different items of general chemistry and its

interpretation based upon the neo-Piagetian theory of Pascual-Leone. Journal of Chemical Education, 64, 502-505.

Niaz, M. (1987b). The role of cognitive factors in the teaching of science. Research in Science and Technological Education, 5, 7-16.

Niaz, M. (1988). Manipulation of M-demand of chemistry problems and its effect on student performance: A neo-Piagetian study. Journal of Research in Science Teaching, 25, 643-657.

Niaz, M. (1989a). The relationship between M-demand, algorithms, and problem solving: A neo-Piagetian analysis. Journal of Chemical Education, 66, 422-424.

Niaz, M. (1989b). The role of cognitive style and its influence on proportional reasoning. Journal of Research in Science Teaching, 26, 221-235.

Niaz, M., & Lawson, A.E. (1985). Balancing chemical equations: The role of developmental level and mental capacity. Journal of Research in Science Teaching, 22, 41-51.

Novick, S., & Nussbaum, J. (1978). Junior high school pupils' understanding of the particulate nature of matter: An interview study. Science Education, 62, 273-281.

Nurrenbern, S.C., & Pickering, M. (1987). Concept learning versus problem solving: Is there a difference? Journal of Chemical Education, 64, 508-510.

Pascual-Leone, J. (1969). Cognitive development and cognitive style: A general psychological integration. Unpublished Ph.D. dissertation, University of Geneva.

Pascual-Leone, J. (1988). An organismic process model of Witkin's field-dependence/independence. In Globerson, T., Ed., Cognitive style and cognitive development. Norwood, NJ: Ablex.

Pascual-Leone, J., & Burtis, P.J. (1974). FIT: Figural Intersection Test, A group measure of M-capacity. Unpublished manuscript, York University, Ontario.

Pascual-Leone, J., Goodman, D., Ammon, P., & Subelman, I. (1978). Piagetian theory and neo-Piagetian analysis as psychological guides in education. In Gallagher, J.M., & Easley, J.A., Eds., Knowledge and Development, New York: Plenum.

Pascual-Leone, J., & Niaz, M. (1988). Organismic constraints in science teaching: A neo-Piagetian perspective. Unpublished manuscript, York University, Ontario.

Pascual-Leone, J., & Smith, J. (1969). The encoding and decoding of symbols by children: A new experimental paradigm and a neo-Piagetian model. Journal of Experimental Child Psychology, 8, 328-355.

Renner, J.W. (1982). The power of purpose. Science Education, 66, 709-716.

Roadrangka, V., Yeany, R.H., & Padilla, M.J. (1983). The construction and validation of Group Assessment of Logical Thinking (GALT). Paper presented at the Annual Meeting of the National Association for Research in Science Teaching (NARST), Dallas, April.

Rosnick, P., & Clement, J. (1980). Learning without understanding: The effect of tutoring strategies on algebra

misconceptions. Journal of Mathematical Behavior, 3, 3-28.

Sawrey, B.A. (1990). Concept learning versus problem solving: Revisited. Journal of Chemical Education, 67, 253-254.

Staver, J.R., & Jacks, T. (1988). The influence of cognitive reasoning level, cognitive restructuring ability, disembedding ability, working memory capacity, and prior knowledge on students' performance on balancing equations by inspection. Journal of Research in Science Teaching, 25, 763-775.

Witkin, H.A., Oltman, P.K., Raskin, E., & Karp, S.A. (1971). A manual for the embedded figures test. Palo Alto, CA: Consulting Psychologists Press.

Table 1

Means, Standard Deviations, and Response Frequencies of Subjects in All Items

ITEM 1A

Response	N (%)	Mean (SD)
a	0	0.39 (0.49)
b	3 (5)	
c*	24 (39)	
d	12 (19)	
e	23 (37)	

ITEM 1B

Response	N (%)	Mean (SD)
a*	10 (16)	0.16 (0.37)
b	31 (50)	
c	16 (26)	
d	5 (8)	

ITEM 1C

Response	N (%)	Mean (SD)
a*	54 (87)	0.87 (0.34)
b	2 (3)	
c	1 (2)	
d	5 (8)	
e	0	

ITEM 2A

Response	N (%)	Mean (SD)
a	0	0.18 (0.39)
b	1 (2)	
c*	11 (18)	
d	50 (81)	
e	0	

ITEM 2B

Response	N (%)	Mean (SD)
a	4 (6)	0.61 (0.49)
b	10 (16)	
c	5 (8)	
d*	38 (61)	
e	5 (8)	

ITEM 3A

Response	N (%)	Mean (SD)
a	9 (15)	0.39 (0.49)
b	2 (3)	
c	1 (2)	
d	26 (42)	
e*	24 (39)	

ITEM 3B

Response	N (%)	Mean (SD)
a	5 (8)	0.68 (0.47)
b	10 (16)	
c*	43 (69)	
d	0	
e	4 (6)	

orrect response

Table 2

Correllation Matrix Among All Variables (N = 62)

	GALT	GEFT	FIT	1A	1B[a]	1C	2A	2B	3A	3B
GALT	1									
GEFT	0.57***	1								
FIT	0.35**	0.23	1							
1A	0.24	0.09	-0.03	1						
1B	0.18	0.29*	0.19	0.28*	1					
1C	0.39**	0.11	-0.01	0.11	0.04	1				
2A	0.11	0.10	0.35**	-0.02	0.37**	0.05	1			
2B	0.33**	0.19	-0.09	0.22	-0.01	0.39**	-0.06	1		
3A	0.29*	0.06	0.15	0.25*	0.28*	0.21	0.32**	0.09	1	
3B	0.31*	0.10	0.10	0.05	0.30*	0.15	0.23	0.23	0.27*	1

[a]Figurative items are underlined. ***p = 0.0001, **p < 0.01, *p < 0.05

Table 3

Multiple Regression Summary for Prediction of Success In Experiment 1

	ITEM 1A					ITEM 1B#					ITEM 1C				
Predictor Variable	B Value	Std. Error	R^2	% Var. Expl.	F	B Value	Std. Error	R^2	% Var. Expl.	F	B Value	Std. Error	R^2	% Var. Expl.	F
GALT	0.03	0.01	0.057	5.7	3.61*	-0.00	0.01	0.102	0.1	0.02	0.03	0.01	0.149	14.9	10.51***
FIT	-0.02	0.02	0.072	1.5	0.94	0.01	0.01	0.101	1.5	1.01	-0.02	0.01	0.173	2.4	1.72
GEFT	-0.01	0.01	0.074	0.2	0.15	0.02	0.01	0.086	8.6	5.64**	-0.01	0.01	0.190	1.7	1.20

***$p < 0.005$, **$p < 0.05$, *$p < 0.1$

#Note that for item 1B GEFT enters first into the regression equation followed by FIT and GALT

Table 4

Multiple Regression Summary for Predition of Success in Experiment 2

Predictor Variable	ITEM 2A B Value	Std. Error	R^2	% Var. Expl.	F	ITEM 2B# B Value	Std. Error	R^2	% Var. Expl.	F
FIT	0.04	0.01	0.124	12.4	8.50***	-0.04	0.02	0.160	4.9	3.48*
GEFT	0.00	0.01	0.125	0.1	0.04	0.01	0.01	0.160	0.0	0.01
GALT	-0.00	0.01	0.126	0.1	0.07	0.04	0.01	0.111	11.1	7.47**

$^{***}p < 0.005$, $^{**}p < 0.05$, $^{*}p < 0.1$

#Note that for item 2B GALT enters first into the regression equation followed by FIT and GEFT

Table 5

Multiple Regression Summary for Predition of Success in Experiment 3

Predictor Variable	ITEM 3A B Value	Std. Error	R^2	% Var. Expl.	F	ITEM 3B B Value	Std. Error	R^2	% Var. Expl.	F
GALT	0.03	0.01	0.085	8.5	5.57**	0.03	0.01	0.097	9.7	6.[illegible]5**
GEFT	-0.02	0.01	0.102	1.7	1.15	-0.01	0.01	0.105	0.8	0.55
FIT	0.01	0.02	0.106	0.4	0.22	-0.00	0.02	0.105	0.0	0.00

**$p < 0.05$